Nicholas A. Gage, Ph.D.
Tracy Ulrich, Ph.D.
Lauren Wong, Ph.D.
Nicolette Grasley-Boy, Ph.D.
Nagelle LeBoyd

California Integrated Supports Project

Initial Impacts on Student Outcomes

December 2025

WestEd
WestEd.org

Table of Contents

Abstract

The California Integrated Supports Project (CA-ISP) aims to reduce exclusionary discipline and improve school climate through an integrated framework combining Positive Behavioral Interventions and Supports (PBIS), social and emotional learning (SEL), trauma-informed practices, and culturally sustaining pedagogy. This study employed a quasi-experimental, difference-in-differences (DiD) design using statewide administrative data and a large sample of over 105,000 students to evaluate the impact of CA-ISP implementation on student disciplinary outcomes. Propensity score weighting and multilevel mixed-effects models were used to estimate treatment effects on behavioral incidents, in-school suspensions (ISS), and out-of-school suspensions (OSS), as well as student-reported school climate indicators from the California Healthy Kids Survey (CHKS). Results indicated statistically significant reductions in the likelihood of experiencing any disciplinary incident (odds ratio [*OR*] = 0.597, d = –0.31), ISS (*OR* = 0.641, d = –0.25), and OSS (*OR* = 0.573, d = –0.31) for students in CA-ISP schools. CHKS analyses revealed modest yet significant improvements in student-reported safety (g = 0.10), school connectedness (g = 0.10), and parent involvement (g = 0.11). No effects were found for academic motivation. Findings suggest that CA-ISP holds promise as a scalable framework for promoting equitable disciplinary practices and supportive school climates, though additional instructional supports may be necessary to influence academic engagement. Implications for policy, equity, and future research are discussed.

The California Integrated Supports Project (CA-ISP) was designed to begin supporting the integration of Positive Behavioral Interventions and Supports (PBIS) and school mental health approaches in California schools, providing high-quality professional development in culturally relevant and sustaining practices, trauma-informed practices, and social and emotional learning (SEL).

Funded by the California Department of Education and implemented in collaboration with California's Scaling-up Multi-tiered Systems (SUMS) project (Choi et al., 2022), California PBIS, and state and regional training centers, CA-ISP aims to promote data-driven, equity-centered practices across tiers of prevention and intervention. The model emphasizes cross-sector collaboration, implementation fidelity, and attention to the needs of historically underserved student groups.

CA-ISP supports schools and districts in enhancing Tier 1 (universal), Tier 2 (targeted), and Tier 3 (intensive) interventions by aligning behavioral expectations, discipline policies, and mental health supports. Schools participating in CA-ISP receive professional development, coaching, and technical assistance focused on culturally responsive practices, trauma-informed care, SEL, and systems change. The initiative also emphasizes the use of disaggregated data to monitor equity and guide continuous improvement efforts.

By integrating PBIS with culturally responsive practices, trauma-informed care, SEL, and systems change, CA-ISP seeks to reduce exclusionary discipline, improve student engagement, and promote school climates that support the academic and social and emotional development of all students. While the theoretical foundation for CA-ISP is well supported, empirical research on the initiative's effectiveness is still emerging.

CA-ISP seeks to reduce exclusionary discipline, improve student engagement, and promote school climates that support the academic and social and emotional development of all students

Initial Student Outcome Impacts

Efforts to reduce exclusionary discipline practices and improve school climate have been central to national and state education reform agendas over the past two decades (Losen & Hayes, 2016; Welsh, 2023). Suspensions, particularly out-of-school suspensions (OSS), have been linked to a range of negative academic and behavioral outcomes, including lower achievement, increased dropout risk, and higher likelihood of involvement with the juvenile justice system (Fabelo et al., 2011; Losen et al., 2015). Further, persistent disparities in suspension rates by race, disability status, and other student characteristics have raised concerns about educational equity and civil rights (Cruz et al., 2021; U.S. Department of Education Office for Civil Rights, 2021).

In response to these concerns, many states and districts have adopted Multi-tiered Systems of Support (MTSS) frameworks to improve behavioral outcomes schoolwide and reduce the use of exclusionary discipline (e.g., Gage et al., 2023; Gage et al., 2024). One widely used MTSS framework is PBIS, which promotes proactive strategies for defining, teaching, and supporting appropriate student behaviors to create positive school environments (Sugai & Horner, 2019). Numerous studies have found that schools implementing PBIS with fidelity experience reductions in office discipline referrals (ODRs), suspensions, and other disciplinary infractions (e.g., Bradshaw et al., 2010; Horner et al., 2009).

Despite growing evidence of the positive impacts of PBIS on myriad student and school outcomes (Lee & Gage, 2020), many schools struggle to fully integrate PBIS with mental health supports and broader school improvement efforts to expand the reach of prevention to all students, not only those expressing external behaviors (Barrett et al., 2013). Fragmentation of services and a lack of coordination among school personnel, mental health providers, and families can limit the impact of MTSS on students with mental health needs. In response to these challenges, researchers and policymakers have increasingly advocated for more integrated models that align schoolwide behavioral frameworks with mental health supports and systems-level coordination (Weist et al., 2022).

Core Interventions and Training Structures

Broadly, CA-ISP draws upon three interrelated frameworks. SEL is foundational, guided by the Collaborative for Academic, Social, and Emotional Learning (CASEL) model, which promotes self-awareness, self-management, social awareness, relationship skills, and responsible decision-making (CASEL, 2020).

The project also incorporates culturally relevant and sustaining pedagogy as described in the PBIS Cultural Responsiveness Field Guide (Bal et al., 2021), which emphasizes safety, empowerment, transparency, and responsiveness to cultural and historical context. A third essential framework is trauma-informed practice, informed by the Substance Abuse and Mental Health Services Administration's (SAMHSA's) (2014) recommendations for ensuring psychological and physical safety, trust, collaboration, and cultural responsiveness in organizational settings.

CA-ISP is organized around five foundational domains: Identity, Voice, Supportive Environment, Situational Appropriateness, and Data for Equity.

CA-ISP delivers structured, multi-tiered professional development organized around five foundational domains: Identity, Voice, Supportive Environment, Situational Appropriateness, and Data for Equity. These domains represent core entry points for addressing the systemic drivers of inequity in school systems and are designed to promote culturally affirming, trauma-informed, and inclusive practices across all levels of a school's MTSS and PBIS framework. Each domain anchors a set of learning modules and implementation strategies that are grounded in research and tailored to address the local context and student population. School-based leadership teams engage in a facilitated needs assessment process, often using data disaggregated by student subgroups (e.g., race and ethnicity) and implementation fidelity measures (e.g., the Tiered Fidelity Inventory, McIntosh et al., 2016) to determine which domain-specific practices are most relevant to their improvement goals. School-based teams then select from a suite of modular professional learning units—each designed to be practical, evidence-informed, and adaptable to the school's instructional and cultural context. These modules are delivered through a cycle of learning, application, coaching, and reflection, ensuring that professional development is not only theoretically sound but also integrated into daily school routines. This adaptive, site-responsive approach allows schools to build internal capacity while addressing locally identified gaps in student outcomes, school climate, and equity-related measures. The use of local data to drive module selection ensures alignment between the professional development content and the lived realities of the school community, thereby increasing both relevance and sustainability.

CA-ISP emphasizes the foundational role of cultural self-awareness and affirmation in fostering inclusive school environments in the Identity domain. Educators are supported in critically examining their own cultural frameworks, values, and behavioral expectations, with particular attention to how these may diverge from those held by the students and families they serve. This reflective work is not merely personal; it is positioned as essential to dismantling deficit perspectives and fostering equity-oriented pedagogy. One of the central practices in this domain is the *Personal Matrix* activity (Muldrew & Miller, 2021), in which educators map out and analyze the implicit norms that shape their instructional and disciplinary expectations. Through this process, they are prompted to identify where mismatches between home and school cultures may lead to misunderstanding, misbehavior, or

marginalization. The activity encourages staff to reframe such mismatches not as deficits on the part of students, but as opportunities to adapt practices, adjust expectations, and build bridges across cultural differences.

Another core intervention, *My Name, My Identity*, invites students and staff to share the stories, meanings, and cultural significance of their names. This activity positions identity as both relational and narrative, offering a structured way to elevate diverse histories, languages, and traditions within the school community. In addition to deepening empathy and connection, this practice fosters a climate of respect for linguistic diversity and counters the historical erasure of students' cultural identities within institutional spaces, such as schools (Paris & Alim, 2017).

To further embed affirming practices into daily school life, the *Positive Sayings* strategy encourages the adoption of uplifting language and culturally resonant affirmations. Staff are invited to reflect on phrases that have had personal meaning in their own lives and consider how such language might be used to support students' self-concept and sense of belonging. These sayings are then integrated into classroom routines, visual displays, and schoolwide communication systems, reinforcing a climate of warmth, care, and cultural validation. Together, practices within the Identity domain are designed not only to celebrate difference but to actively disrupt exclusionary norms and replace them with inclusive, affirming, and community-rooted approaches to teaching and learning.

The Voice domain aims to dismantle hierarchical structures by embedding mechanisms for participation.

The Voice domain focuses on cultivating inclusive decision-making processes and enhancing student agency, with a particular emphasis on shifting traditional power dynamics in schools. At its core, this domain recognizes that students and families bring critical knowledge, experiences, and perspectives that are essential to equitable school improvement. Practices in this domain aim to dismantle hierarchical structures by embedding mechanisms for participation and co-leadership across educational settings.

A central practice within the Voice domain is the implementation of student-led conferences. In contrast to traditional parent–teacher conferences that often marginalize student input, these sessions invite learners to curate a portfolio of their academic work, reflect on their progress, and lead discussions about their learning goals. This practice fosters metacognition, strengthens self-advocacy, and reinforces students' roles as active participants in their educational journeys

(Tholander, 2011). Moreover, student-led conferences create a more equitable space for caregiver engagement, positioning families as collaborative partners rather than passive recipients of information. When implemented with fidelity, this approach has been associated with increased student motivation, stronger home–school connections, and improved academic outcomes (Mager & Nowak, 2012).

In addition to formal conferencing structures, the use of classroom-based community circles serves as a powerful tool for cultivating relational trust, emotional safety, and peer belonging. These circles are facilitated using affective language and focus on building shared norms, processing emotions, and resolving conflict in a restorative manner. The regular practice of community circles allows students to experience school as a participatory space, one in which their voices are not only heard but valued as essential to the collective well-being of the classroom.

To deepen the impact of these relational practices, educators also engage in professional learning designed to enhance family engagement at the classroom level. This training introduces strategies that promote reciprocal communication, culturally responsive outreach, and sustained relationship building with caregivers and community members. Emphasis is placed on shifting from one-directional information sharing to partnership, particularly with families from historically underserved communities. By building educators' capacity to co-create educational experiences with students and families, practices in the Voice domain contribute to the development of more democratic and inclusive school cultures.

The Supportive Environment domain equips educators with tools to strengthen relational trust and to create learning environments that affirm student dignity and identity.

The Supportive Environment domain focuses on the intentional cultivation of emotionally safe, respectful, and inclusive school climates. Recognizing that students' academic success and behavioral engagement are deeply shaped by their perceptions of safety and belonging, this domain equips educators with tools to strengthen relational trust and create learning environments that affirm student dignity and identity. Practices within this domain are grounded in the principles of positive behavior support and trauma-informed care, with an emphasis on preventive strategies, relational consistency, and responsiveness to students' emotional and cultural needs.

One key strategy within this domain is the use of *WISE Feedback*, an evidence-based method of communication that reinforces high expectations while also affirming students' potential for growth (Yeager et al., 2014). Unlike generic praise or corrective feedback that can be perceived as judgmental or insincere, WISE Feedback integrates three critical components: expressing belief in the student's ability to succeed, highlighting the importance of the task, and offering specific, actionable guidance. This feedback approach not only enhances motivation and engagement but also mitigates stereotype threat by explicitly communicating that high standards are grounded in a belief in the student's capacity to meet them.

To support consistency and equity in high-stakes or emotionally charged moments, school staff are also trained to develop and implement neutralizing routines. These routines function as pre-planned, non-escalatory responses that staff can rely on during predictable vulnerable decision points—instances in which implicit bias may influence disciplinary or instructional decisions. By scripting responses in advance and practicing them as a team, educators increase their readiness to respond calmly, fairly, and consistently in ways that preserve student dignity and reduce disparities in exclusionary discipline practices. These routines are particularly critical for preventing the disproportionate use of punitive consequences for racially diverse students and other historically marginalized groups (McIntosh et al., 2018).

Another relational strategy that schools can adopt under the Supportive Environment domain is the use of daily positive greetings at the door. This simple but powerful practice involves teachers greeting each student individually as they enter the classroom, using verbal affirmation, eye contact, and body language to convey respect and care. Research shows that this practice contributes to stronger teacher–student relationships, improved classroom behavior, and increased student engagement throughout the day (Cook et al., 2018). As an added benefit, it provides educators with a daily opportunity to conduct informal wellness checks, notice mood or affective shifts, and offer early support to students who may be struggling.

Collectively, the strategies in the Supportive Environment domain are designed not only to prevent behavioral challenges but to build a schoolwide culture rooted in connection, affirmation, and emotional safety. By embedding these practices into daily routines and professional expectations, schools participating in CA-ISP take meaningful steps toward creating conditions where all students feel seen, supported, and ready to learn.

Situational Appropriateness encourages a culturally reflective stance—one that recognizes how dominant norms may marginalize or pathologize students.

The Situational Appropriateness domain invites school teams to interrogate the extent to which institutional expectations, behavioral norms, and instructional practices align with the cultural contexts and lived experiences of their students and families. Rather than assuming a universal standard for what constitutes appropriate behavior or engagement, this domain encourages a culturally reflective stance—one that recognizes how dominant norms may marginalize or pathologize students whose backgrounds diverge from mainstream expectations. The work begins with a critical review of the school's existing behavioral expectations and matrices, including the language, structure, and underlying

assumptions embedded within them. Teams are guided to ask whether the expectations reflect the values, communication styles, and community norms of the students they serve, and whether they create opportunities for all students to succeed without requiring integration into a narrow behavioral code.

To support this process, school teams revise their expectations and teaching matrices to better reflect the voices and perspectives of students, families, and local communities. This often involves gathering input through focus groups, surveys, or co-designed sessions with interest holders from historically marginalized populations. As part of this revision process, teams also work to explicitly define staff roles within the matrix, outlining how adults are expected to model and reinforce each behavioral expectation. By doing so, the school community increases clarity and consistency in implementation while also reinforcing shared accountability for cultivating an inclusive climate.

This focus on cultural congruence and adult modeling is rooted in the principles of culturally sustaining pedagogy, which seeks not merely to recognize student differences but to honor and sustain the cultural and linguistic identities of students within the fabric of school life (Paris & Alim, 2017). When applied with fidelity, these practices help shift the focus from student compliance to community alignment, creating a behavioral framework that supports both equity and belonging. In doing so, the Situational Appropriateness domain functions as a bridge between policy and practice, ensuring that school rules are not only clearly articulated but also affirmatively grounded in the cultural realities of the communities they are intended to serve.

Data for Equity emphasizes the use of disaggregated data as a catalyst for systemic reflection and targeted action.

The Data for Equity domain equips school teams with the knowledge, tools, and routines necessary to identify, interpret, and respond to patterns of disproportionality in educational outcomes, particularly those related to student discipline, attendance, and academic engagement. This domain emphasizes the use of disaggregated data—not simply as a compliance tool—as a catalyst for systemic reflection and targeted action. School teams are trained to move beyond surface-level reporting toward deeper analysis that interrogates how race, disability status, language background, and other intersecting identities may influence students' experiences in school. Central to this work is a four-step equity-centered problem-solving model that guides teams through the process of identifying gaps, diagnosing root causes, selecting evidence-based interventions, and monitoring progress over time. This model helps ensure that data-driven decision-making remains anchored in equity and focused on transformation rather than remediation.

A critical focus within this domain is the identification and mitigation of the vulnerable decision points—specific situations, times of day, locations, or behavioral categories—where implicit bias is more likely to influence adult decision-making, as described above. Through structured reflection and analysis of site-level data, educators are supported in pinpointing where these vulnerable moments occur and designing neutralizing routines that can interrupt bias in real-time. These routines, often co-developed by leadership teams and frontline staff, serve as pre-planned scripts or actions

that help educators respond consistently and equitably, particularly in high-stress or subjective decision-making scenarios (McIntosh et al., 2018).

In parallel, educators engage in a systematic review of their school's policies, classroom norms, and disciplinary procedures to identify embedded biases and inequitable assumptions. This process is grounded in the principle that equity must be built into the system's structure, not appended to it. As such, staff are encouraged to collaborate with students and families—particularly those from historically marginalized communities—to revise rules, expectations, and protocols in ways that reflect shared values and lived experiences. These co-design efforts not only ensure cultural responsiveness but also strengthen relational trust and community accountability.

The emphasis on transparency and continuous improvement is a defining feature of the Data for Equity domain. Schools are encouraged to establish regular data review cycles, publicly share findings, and track implementation fidelity to their equity action plans. By embedding these practices into the fabric of school improvement efforts, CA-ISP promotes a shift from reactive, compliance-oriented data use toward a more intentional, justice-centered approach. Ultimately, the goal of this domain is to equip educators with the skills and mindsets to not only uncover inequities but to address them through sustained, strategic, and collaborative action.

The implementation model used by the CA-ISP is grounded in a cascading framework of professional learning and sustained, embedded coaching. This approach reflects a core commitment to capacity building at all levels of the educational system—from district leadership to classroom practice—and is designed to promote both scalability and sustainability of evidence-based, equity-centered practices. The model begins with intensive training for district and site leadership teams, who receive direct support from regional technical assistance providers. These initial trainings introduce the foundational content areas of the project—culturally sustaining pedagogy, SEL, trauma-informed practices, and data for equity—and are structured to prepare leaders to guide coherent implementation within their local contexts.

Site-based leadership teams are then responsible for completing approximately 15 hours of structured professional development, typically delivered across multiple sessions. These trainings are organized into three interrelated units: Voice, Identity, and Data for Equity. The content is highly interactive and inquiry-driven, emphasizing systems thinking, shared leadership, and critical reflection. Upon completing this foundational learning, site teams are tasked with facilitating professional learning for all school staff through a series of modular trainings. Each module is approximately 45 minutes in length and focuses on a specific strategy or practice aligned with the five core CA-ISP domains. Site teams select modules based on their local needs, using disaggregated data and team-based planning tools to determine the most relevant content. Modules are typically embedded into pre-existing professional development routines, such as staff meetings, grade-level team time, or dedicated professional learning days, ensuring alignment with ongoing improvement efforts.

To support high-quality implementation, CA-ISP integrates a multi-tiered coaching infrastructure designed to provide continuous feedback, observation, and modeling. Coaching occurs at multiple levels: district coordinators provide oversight and technical assistance to site-based implementation teams, while site coaches or teacher leaders offer job-embedded support to classroom educators. Coaches are trained to use equity-centered implementation tools to assess progress and inform next steps, including structured fidelity checklists, practice walkthroughs, and reflective debriefs with educators. These coaching routines ensure that professional development content is not theoretical but translated into consistent, observable changes in practice.

Coaching and implementation activities are further supported by tools, such as the National Implementation Research Network (NIRN) Hexagon Tool (Metz et al., 2019) and the California-specific Local Education Agency Systems Analysis (LEASA) tool. The Hexagon Tool enables teams to assess the contextual fit and readiness of practices before adopting them, while the LEASA process supports ongoing systems analysis to monitor implementation stages, interest holder engagement, and resource alignment. These tools encourage a deliberate, data-driven approach to change management, helping teams avoid common implementation pitfalls such as initiative fatigue, misalignment, or superficial compliance.

CA-ISP fosters a culture of continuous improvement grounded in equity, collaboration, and shared accountability.

Together, the cascading professional learning structure, targeted coaching supports, and use of evidence-based implementation tools increase the likelihood that CA-ISP is feasible and sustainable in practice. By building internal capacity and distributing leadership across the system, the model fosters a culture of continuous improvement grounded in equity, collaboration, and shared accountability. With coaching, data-driven planning, and structured implementation routines, CA-ISP supports school teams in improving climate, reducing disparities, and advancing positive outcomes for all students.

MTSS, PBIS, and Discipline Outcome Evidence

Extensive research supports the association between PBIS implementation and improved discipline outcomes. For example, Bradshaw et al. (2010) found that schools implementing schoolwide PBIS experienced significantly lower rates of ODRs and suspensions compared to control schools. Similarly, Horner et al. (2009) reported reductions in problem behavior and improvements in perceived school safety in PBIS schools. A meta-analysis of all group experimental and quasi-experimental evidence supporting the effectiveness of

PBIS found a significant impact on reducing disciplinary exclusions (*g* = 0.25; Lee & Gage, 2020).

More recent studies have highlighted the importance of implementation fidelity and contextual factors (e.g., Gage et al. 2024). McIntosh et al. (2016), Gage et al. (2019), and Lee et al. (2021) all found that fidelity to PBIS practices was positively associated with reductions in racial disparities in discipline. However, they also noted that PBIS alone may not be sufficient to address entrenched inequities without explicit focus on equity and cultural responsiveness. These findings have spurred increased interest in integrated models that combine MTSS with mental health and equity initiatives.

A growing body of research supports the effectiveness of schoolwide MTSS in improving school climate and student mental health outcomes. Studies have consistently found that implementation of MTSS frameworks—particularly those integrating SEL and mental health supports—is associated with improvements in students' perceptions of safety, connectedness, and emotional well-being. For example, Cook et al. (2015) reported significant improvements in school climate and reductions in internalizing symptoms among students attending schools that implemented a comprehensive SEL-enhanced MTSS model. Similarly, Barrett et al. (2018) documented improvements in student well-being, school engagement, and access to mental health services following the districtwide implementation of tiered systems integrating PBIS and school mental health.

Meta-analyses reinforce these findings. Sklad et al. (2012) found that universal SEL programs had small to moderate positive effects on student mental health, including reductions in anxiety, depression, and emotional distress. More recently, Wiglesworth et al. (2020) highlighted the role of school climate as a mediator in the relationship between whole-school SEL interventions and student mental health outcomes. These findings underscore the value of schoolwide systems that not only support behavioral expectations but also promote emotional safety and belonging—key protective factors for youth mental health (O'Malley et al., 2015).

Recent implementation studies have emphasized the importance of fidelity, leadership support, and data-based decision-making in sustaining these outcomes (Forman et al., 2013; Weist et al., 2022). However, researchers also caution that MTSS efforts focused solely on behavioral indicators may fall short if they do not explicitly address emotional well-being, trauma, and social identity factors. As a result, there is increasing interest in integrated frameworks such as the

Interconnected Systems Framework (ISF), which explicitly merges school mental health and PBIS within an MTSS structure to promote equity, access, and comprehensive supports (Barrett et al., 2013; Hoover et al., 2020).

Integrated MTSS, PBIS, and School-based Mental Health Models

Integrated frameworks, such as the ISF, have emerged as promising models for unifying schoolwide behavioral support systems like PBIS with mental health promotion and intervention strategies (Barrett et al., 2013). ISF emphasizes shared leadership, cross-sector collaboration, data-driven decision-making, and the alignment of school and community-based mental health services to improve student outcomes and school climate (Barrett et al., 2013; Eber et al., 2019). Recent studies have demonstrated ISF's positive impact on school environments. In a large-scale randomized controlled trial, Splett et al. (2024) found that schools implementing ISF reported significantly greater improvements in perceptions of student engagement among both students ($g = 0.47$) and school staff ($g = 0.92$), as well as more equitable and consistent disciplinary practices as rated by teachers ($g = 0.91$). These effects exceeded those found for PBIS-only conditions, suggesting that the integration of mental health within MTSS structures may enhance the overall relational quality and equity orientation of school environments.

Additional evidence from a quasi-experimental study by Weist et al. (2022) further supports ISF's impact on mental health-related outcomes. In this two-year evaluation across 36 schools, ISF implementation was associated with statistically significant improvements in overall school climate ($p < .05$) and perceptions of mental health support availability. Schools that received ISF also demonstrated increased use of universal mental health screening and greater access to tiered supports. The study emphasized the importance of capacity-buildingactivities such as teaming structures, community partnerships, and professional development to sustain improvements in both climate and student well-being.

> *CA-ISP aims to enhance schools' capacity to create equitable, inclusive environments that support the whole child.*

Although ISF is not currently implemented statewide in California, CA-ISP represents a significant step toward building a scalable, integrated MTSS framework tailored to the state's context. While CA-ISP differs structurally from ISF (e.g., CA-ISP does not focus on bringing external mental health providers into schools like ISF does), it similarly promotes SEL, culturally sustaining practices, and trauma-informed systems change. It aims to enhance schools' capacity to create equitable, inclusive environments that support the whole child. However, to date, no outcome evaluations of CA-ISP have been conducted. As California continues to scale integrated MTSS models, the accumulating evidence base on ISF underscores the potential benefits of combining behavior, SEL, and mental health supports into

a unified system to improve climate, reduce disparities, and promote mental wellness at scale.

Current Study Purpose

This study seeks to examine the impact of CA-ISP participation on student-level disciplinary outcomes using a quasi-experimental, DiD framework. Specifically, we analyze changes in behavioral incident counts, in-school suspensions (ISS), and out-of-school suspensions (OSS), as well as whether students received any such disciplinary actions. By leveraging statewide administrative data and applying rigorous statistical controls, this study provides one of the first large-scale examinations of CA-ISP's effects on exclusionary discipline practices.

Our analyses aim to answer the following research question: To what extent is CA-ISP participation associated with reductions in the frequency and likelihood of disciplinary incidents, ISS, and OSS among California students? By addressing this question, we contribute to the growing body of research on integrated behavioral and mental health frameworks and provide actionable insights for policymakers and practitioners seeking to reduce disparities and improve outcomes for all students.

Method

Sample

We collected student-level data from all partner school districts participating in CA-ISP. We requested data from all schools in each partner school district. This included schools not participating in the CA-ISP so that we could create a comparison group. We received these student-level data from 20 school districts, 192 schools, and 139,124 students for three consecutive school years (2021–2022, 2022–2023, and 2023–2024). However, only eight school districts provided data for the 2021–2022 school year, so we removed that year from the analytic dataset. We then merged the student-level analytic dataset with two school-level datasets. First, we merged the student data with the U.S. Department of Education National Center for Education Statistics Common Core of Data (CCD) from the 2023–2024 school year. These data provide school demographic characteristics, including charter status, urbanicity, enrollment, and race and ethnicity information. We then merged the dataset with school-level data from the California Department of Education, including school-level reading achievement and the percentage of students receiving English Learner services and special education services. After cleaning and merging, the dataset included over 105,000 students each year from 183 schools.

We focused our analyses on the effects of one year of CA-ISP implementation on student outcomes for Cohort 1. Therefore, we excluded the schools that participated in the pilot study that received CA-ISP training and schools in Cohort 2 because they did not receive CA-ISP implementation until after the 2023–2024 school year. We also removed students who moved between schools to ensure that we estimated a treatment-on-the-treated (ToT) effect. Table 1 in the Appendix provides the demographic characteristics of the students and schools in Cohort 1 (i.e., treatment group) and the schools within partner districts that did not participate in CA-ISP (control group). We received student-level data from 28 schools that participated in Cohort 1 training. The majority of these schools (84%) were elementary schools in suburban locales (85%). Overall, just over 60 percent of students were eligible for free or reduced-price lunch, 48 percent of students were Hispanic, 24 percent were White, 9 percent were Black, and 25 percent received English Learner services. The treatment schools were similar demographically to the control schools, except that the control schools were more likely to be middle and high schools.

We also collected the student-level California Healthy Kids Survey (CHKS) data for all elementary students in California for the 2023–2024 school year. Not all schools participated in the CHKS data collection, so not all partner district schools were present in the CHKS dataset. Additionally, the CHKS is completely anonymous. Therefore, we could not match student CHKS responses to any of the student-level district data. We created a separate dataset for CHKS analyses, but matched student-level data with the same school-level datasets described above. The final analytic dataset included data from 314 school districts, 1,767 schools, and 98,870 students. Of those, 1,255 students in 25 schools from 19 school districts participated in CA-ISP.

Dependent Measures

Behavioral outcomes were collected from each school district's submission to California Longitudinal Pupil Achievement Data System (CALPADS), the state's longitudinal data warehouse that collects and maintains individual-level student data. We examined three categories of behavioral outcomes, each represented on both continuous (count) and binary (indicator) scales, aligned with state reporting definitions and education codes.

Total number of behavioral incidents. This continuous measure reflects the total number of student behavior incidents reported during the academic year. Incidents may include defiance, disruption, physical altercations, bullying, or violations of school policies as outlined in California Education Code § 48900. Incident data were drawn from the CALPADS Student Incident Result (SIRS) file, following standardized definitions for reportablebehaviors. A binary version (any behavioral incident) was also created, coded as 1 if a student had ≥1 incident and 0 otherwise.

In-school suspension. ISS data capture the number of school days a student was removed from their regular instructional setting and assigned to an in-school suspension environment (e.g., a supervised classroom or isolation space). These removals are reported to CALPADS when they result from behavior defined in California Education Code § 48911.1. We used a continuous measure (days of ISS) and a binary indicator (1 = any ISS; 0 = none) as recorded in the CALPADS Discipline file.

Out-of-school suspension. OSS outcomes reflect the number of days a student was removed from school grounds for disciplinary reasons under California Education Code § 48900–48915. This includes suspensions for physical injury, drug-related offenses, or other major infractions. OSS counts were drawn from the Discipline Action data element in CALPADS. We again included both the continuous measure (total days) and a binary indicator (any OSS during the year).

Each of these outcomes was selected to reflect both the occurrence and intensity of behavioral discipline experienced by students, enabling a multidimensional understanding of student behavior and school disciplinary practices.

California Healthy Kids Survey. The CHKS is a statewide, school-based survey developed by WestEd in collaboration with the California Department of Education to assess students' health behaviors, school climate, and social and emotional well-being. The CHKS is designed for students in grades 5, 7, 9, and 11 and includes validated measures related to substance use, mental health, school connectedness, perceived safety, and developmental supports (WestEd, 2023). The survey is anonymous, voluntary, and typically completed online during the school day.

For the present study, we used data from the 2023–2024 CHKS administration of the elementary Core Module. The elementary version of the CHKS is a simplified, developmentally appropriate instrument designed specifically for 5th grade students. It focuses on topics such as school connectedness, perceived safety, caring adult relationships, bullying and harassment, and basic health behaviors (e.g., nutrition, physical activity). It avoids sensitive content related to substance use and mental health symptoms, recognizing that younger students may not yet encounter or understand these topics. The language is written at approximately a 3rd to 4th grade reading level, and the format often includes simpler question structures and fewer response options (e.g., yes or no or three-point scales). Although designed for 5th grade, many elementary schools include students in grades 3 to 5 based on the data. The multi-item scales and reliability estimates are presented in Table 2.

Data Analysis

Disciplinary Exclusions

Missing data imputation. To address missing data on student- and school-level covariates, we implemented multiple imputation using the Multivariate Imputation by Chained Equations (MICE) approach in R (van Buuren & Groothuis-Oudshoorn, 2011). We imputed the following variables based on missingness and theoretical relevance to the analysis: student grade level, gender, race and ethnicity, English Learner (EL) status, special education status (SWD), school urbanicity, school level, free or reduced-price lunch eligibility (FRPL), total school enrollment, and prior school-level English language arts (ELA) achievement.

Categorical variables were converted to factors, and predictive mean matching (PMM) was used as the imputation method for all variables to preserve the distributional properties of the data. We generated five imputed datasets (*m* = 5) using a random seed of 123 for reproducibility. For the primary analysis, we selected the first completed dataset as representative. This dataset was then recombined with the original dataset for analysis. This imputation strategy enabled us to retain the full analytic sample while reducing potential bias due to listwise deletion.

Propensity score weighting. To reduce bias due to non-random treatment assignment (i.e., quasi-experimental design), we estimated inverse probability of treatment weights (IPTW) using propensity scores calculated separately for each academic year. This year-stratified approach accounted for potential differences in covariate distributions across years, consistent with best practices in longitudinal observational data (Austin & Stuart, 2015).

We estimated year-specific propensity scores via logistic regression models, predicting treatment assignment based on student- and school-level covariates. These included student grade level, gender, race and ethnicity, EL status, SWD, urbanicity, school level, eligibility for FRPL, total school enrollment, and the 2021–2022 school-level ELA performance. The models were fit separately for each academic year, and predicted probabilities (propensity scores) were assigned back to individual records. The matched dataset was used for all subsequent analyses to reduce potential confounding effects and ensure comparability between groups and ensure that the analyses met WWC standards with reservations.

We then calculated stabilized IPTWs as follows: for treated students, weights were computed as the inverse of the predicted propensity score (1/PS); for control students, the weights were the inverse of one minus the propensity score [1/(1 - PS)]. These weights were applied in all subsequent DiD analyses described below to create a pseudo-population in which treatment assignment was independent of observed covariates, facilitating unbiased estimation of treatment effects under the assumption of no unmeasured confounding.

Transforming dependent variables. Initial examination of the distributional properties of the outcomes revealed substantial positive skewness, particularly for disciplinary absences and incident counts (see Table 2). To address these issues, we explored a series of common monotonic transformations, including the square root, cube root, and natural log of the outcome (using log1p() to accommodate zero values). While both the square root and cube root transformations reduced skewness to some extent, the log transformation consistently produced the largest reductions, particularly for the most extreme cases. For instance, the skewness of Behavior Incidents dropped from 9.93 to 3.12 under log1p(). Therefore, we used the log transformation for all county outcomes because it reduced skewness while preserving the interpretability of the resulting models. Reducing skewness enhances the validity of statistical inferences from linear models, which assume normally distributed residuals. Consistent with prior methodological guidance (e.g., Osborne, 2010), we prioritized transformations that brought skewness below a threshold of ±2 when feasible.

Treatment effect models. To assess the extent of clustering in the data, we first estimated unconditional (intercept-only) linear mixed-effects models for each of the three continuous log-transformed outcomes: total disciplinary

incidents and days missed for ISS and OSS. Each model included random intercepts for both school and district. Intraclass correlation coefficients (ICCs) were computed to quantify the proportion of outcome variance attributable to school and district-level clustering. The ICC for total disciplinary incidents was 0.252, indicating that approximately 25 percent of the variance occurred at the school or district level. The ICCs were considerably smaller for days missed for ISS absences (0.009) and days missed for OSS (0.067), suggesting that most of the variability in these outcomes occurred at the individual level.

We then estimated a series of DiD models to evaluate the schoolwide impacts of the CA-ISP project on student-level behavior. We used weighted linear mixed-effects regression models for the total number of incidents and days missed for ISS and OSS and the weighted logistic mixed-effects models for the likelihood of receiving at least one ISS or OSS. We log-transformed all three counts of these outcomes to address right skew and zero inflation in the original count distribution (Atkins & Gallop, 2007; Feng et al., 2014)[1]. The main independent variables were an indicator for treatment group (1 = intervention, 0 = control), a binary time indicator (0 = baseline year [2022–2023], 1 = intervention year [2023–2024]), and their interaction. The interaction term (treatment: time) represents the DiD estimate, isolating the treatment effect beyond temporal trends or group differences. Each model was adjusted for a set of student-level and school-level covariates, including

- student characteristics: grade level (as a factor), gender, race and ethnicity, EL status, and SWD status; and
- school characteristics: urbanicity, school level, proportion of students eligible for FRPL, total enrollment, and the school-level proportion of students meeting ELA proficiency in the baseline year.

Random intercepts were included at the school and district levels to account for clustering. Models were estimated using maximum likelihood with the Laplace approximation and weighted using inverse probability of treatment weights derived from propensity scores to reduce selection bias (Austin & Stuart, 2015), as described above. All models were estimated using lme4 (Bates et al., 2015).

Effect sizes. To facilitate interpretation of treatment effects for the linear mixed-effects models, we calculated standardized mean differences (*d*) for each outcome. The *d*'s were calculated by dividing the estimated DiD interaction coefficient by the standard deviation of the untransformed outcome variable in the control group at baseline (i.e., prior to the intervention) (Bloom et al., 2007; Kraft, 2020).

1 The complexity of the models limited our ability to accurately estimate Poisson and zero-inflated Poisson models.

This approach allows for an effect size metric that is interpretable on a standardized scale, irrespective of outcome transformation or original units.

For each outcome, the standardized mean difference (*d* was calculated using the following formula:

$$d = \frac{\hat{\beta}_{DiD}}{SD_{Control\ baseline}}$$

Where

- $\hat{\beta}_{DiD}$ is the estimated coefficient for the cohort × time interaction term in the model, representing the DiD estimate.
- $SD_{baseline}$ is the standard deviation of the untransformed outcome variable for the baseline (academic year 2022–2023).

This method preserves comparability across outcomes and is appropriate for interpreting practical significance in school-based intervention research, especially when models involve log-transformed count data, like this study.

Effect sizes (*d*) were interpreted using the framework proposed by Kraft (2020), in which

- < 0.05 is considered small,
- 0.05 to 0.20 is modest,
- 0.20 to 0.40 is medium, and
- > 0.40 is large.

For interpretability of the mixed-effects logistic regression models, we calculated odds ratios (*OR*s) by exponentiating the log-odds coefficients. A statistically significant negative coefficient on the treatment-by-time interaction is interpreted as evidence that the intervention was associated with a reduction in the odds of experiencing ISS or OSS, compared to the control group, after adjusting for baseline differences and observed covariates. We then converted the *OR* to *d* using the following formula (Chinn, 2000):

$$d = \frac{\ln(OR)}{1.81}$$

This formula assumes a logistic distribution of the underlying latent continuous variable (such as a propensity for an ISS or OSS). The 1.81 is the approximate standard deviation of the standard logistic distribution.

School climate and well-being. The CHKS analyses were restricted to a single year of data because we could not match student responses from year to year. To establish baseline equivalence between the groups, we added the school-level percentage of students at or above the benchmark in ELA from the 2021–2022 school year. We chose 2021–2022 because this was prior to schools being recruited for the CA-ISP. This approach ensured that we met the WWC evidence standards. Per the WWC (2024), "If the study cannot satisfy the individual-level baseline equivalence standard, satisfying the cluster-level baseline equivalence standard is sufficient instead" (p. 60). Equivalence was established between the treatment (CA-ISP) and comparison groups on the cluster-level baseline measures (*g* = 0.14).

We estimated a series of linear mixed-effects models to examine the association between CA-ISP participation (treatment vs. comparison) and multiple student-reported outcomes related to school climate, well-being, and academic motivation. Each outcome was modeled separately using the lmer() function from the lme4 package in R. All models included the following covariates: student grade (dummy-coded indicators for grades), race and ethnicity, sex, school urbanicity, percentage of students eligible for FRPL, total school enrollment, and school-level racial and ethnic composition (White, Hispanic or Latino, and Black). We also included two school achievement covariates: the percentage of students meeting state standards in ELA in 2020–2021 and 2021–2022.

To account for the nested structure of the data, with students clustered within schools and schools nested within districts, we specified a two-level hierarchical linear model that included random intercepts for school and district. This approach allowed for the partitioning of variance attributable to between-school and between-district differences and produced more accurate standard errors for fixed effects. Model parameters were estimated using restricted maximum likelihood (REML), which provides unbiased estimates of variance components in mixed-effects models. Degrees of freedom and *p*-values for fixed effects were computed using Satterthwaite's approximation, as implemented in the lmerTest package in R. All models were estimated using the lme4 package in R (Bates et al., 2015).

To facilitate interpretation of the intervention effects, we calculated standardized mean difference (*g*) effect sizes for statistically significant treatment effects. Effect sizes were computed by dividing the unstandardized regression coefficient for the treatment indicator by the standard deviation of the outcome variable among students in the comparison group. This approach provides a scale-free estimate of group differences, expressed in standard deviation units. All *g*'s were based on the raw, unweighted distribution of outcomes and reflect covariate-adjusted estimates derived from the mixed-effects models. This method aligns with reporting recommendations from the WWC (WWC, 2024), which emphasize the use of interpretable, standardized metrics to convey the magnitude of program effects in educational evaluations.

Results

Disciplinary Incidents

The linear mixed-effects model evaluated the impact of CA-ISP on students' disciplinary incidents using the log-transformed number of incidents and a DiD framework. The primary coefficient of interest was the interaction term between treatment group and time, which estimates the differential change in disciplinary incidents over time for the intervention group relative to the control group. The model included all available student and school covariates and the IPTW. The estimated coefficient for the interaction term for the disciplinary incident model was statistically significant and negative: $\beta = -0.086$, $p < .001$ (see Table 3). This suggests that students in the intervention group experienced a statistically significantly greater reduction in the log-transformed number of disciplinary incidents compared to control students from the baseline to the intervention year.

To interpret the effect on the original (non-logged) scale, we exponentiate the coefficient (0.92). This result suggests that the intervention was associated with an 8.2 percent reduction in the number of disciplinary incidents relative to the control group over time. To express this effect as a standardized mean difference (*d*), we convert the log-scale coefficient into raw units and divide this by the standard deviation of the outcome for the control group in the baseline year (SD = 4.87), resulting in d = –0.02, which is considered a small effect.

Next, we estimated a weighted logistic DiD model predicting whether a student had any behavioral incident during the school year. The model included fixed effects for treatment cohort, post-treatment period, their interaction, and covariates, including student demographics, school-level characteristics, and prior academic achievement. Random intercepts were included for school and district to account for clustering. The results are presented in Table 4.

The interaction between treatment cohort and post-treatment period was statistically significant, indicating that students in the treatment group experienced lower odds of having a behavioral incident after program implementation compared to the control group, ß = –0.5148, p < .001. The odds ratio (*OR* = 0.597) suggests that the odds of a behavioral incident were 40.3 percent lower for students in the treatment group in the post-treatment year relative to their pre-treatment odds and compared to the control group. To aid interpretation, we converted the *OR* to *d*, which yielded d = –0.305. This falls within the medium effect size range according to Kraft's (2020) benchmarks for interpreting effects in education research.

In-school Suspension

Again, we estimated a DiD linear mixed-effects model to evaluate the impact of CA-ISP on the log-transformed number of days students were absent due to ISS. The model included fixed effects for student demographics, school characteristics, and baseline school-level academic performance, with random intercepts for school and district to account for clustering. The outcome variable was log-transformed using log1p() to reduce skew and preserve zero values. The results are presented in Table 5. The interaction term between cohort and time, representing the treatment effect, was statistically significant (ß = -0.0065, p < .001), suggesting that students in the treatment schools had fewer days absent due to ISS in 2023–2024 compared to students in control schools, after accounting for covariates.

We exponentiated the coefficient (0.99) to interpret the effect on the original (non-logged) scale. The results suggest that CA-ISP was associated with a 1 percent reduction in the number of days missed due to ISS relative to the control group over time. We also calculated *d* using the standard deviation of the untransformed outcome in the control group during the baseline year (SD = 0.187), finding d = -0.04.

Next, we estimated a weighted logistic mixed-effects model to assess the impact of CA-ISP on the likelihood of receiving any ISS (see Table 6). The interaction term between treatment and time was statistically significant (ß = −0.444, p <.001), suggesting that students in the treatment schools had significantly lower odds of receiving any ISS in 2023–2024 relative to their matched comparison peers. The *OR*

associated with the interaction term was 0.641, indicating a 35.9 percent reduction in the odds of experiencing any ISS post-intervention, holding other variables constant. When converted to *d*, the effect size is -0.25, which is a medium effect.

Out-of-school Suspension

To examine the effect of CA-ISP on student absences due to OSS, we estimated a weighted linear mixed-effects DiD model with log-transformed OSS absence days as the dependent variable. Similar to the prior models, we included fixed effects for student demographic characteristics, school-level covariates, and an interaction between cohort assignment and post-treatment time (i.e., 2023–2024). Random intercepts were specified for schools and districts to account for clustering, and inverse probability weights were applied to adjust for baseline covariate imbalance (see Table 7).

Once again, the interaction between treatment cohort and post-treatment year was statistically significant (ß = −0.031, <.001). This coefficient indicates that, relative to the control group, students in the treatment schools experienced a reduction in OSS absences following the intervention. After back-transforming the coefficient from the log scale, the estimated effect translates to a reduction of approximately 0.03 OSS days per student. To contextualize the magnitude of this effect, we again computed d using the control group's untransformed standard deviation of OSS absences (*SD* = 1.23), resulting in *d* = −0.03.

Finally, we estimated a logistic mixed-effects model to examine whether CA-ISP was associated with the likelihood of receiving any OSS. The results are presented in Table 8. The interaction between treatment and time was statistically significant (ß = −0.556, *p* <.001), with an odds ratio of 0.573. This result suggests that the intervention cohort had 42.7 percent lower odds of experiencing an OSS in the post-intervention period compared to the control group. When converted to *d*, the effect size is -0.31, which is a medium effect.

California Healthy Kids Survey

Results from the linear mixed-effects models are summarized in Table 10 Participation in the Cohort 1 intervention was significantly associated with improvements in several key student-reported outcomes. Specifically, students in Cohort 1 reported greater feelings of safety (ß = 0.036, *p* = .049), corresponding to an SMD of 0.10, and a stronger sense of school belonging as measured by the high connectedness scale (ß = 0.027, *p* = .046; *SMD* = 0.10). These effects, while modest in magnitude, are consistent with other school-based SEL interventions and suggest that the program contributed meaningfully to students' perceptions of a safe and supportive school environment.

Additionally, students in Cohort 1 reported higher levels of parent involvement (ß = 0.029, *p* = .015), with an associated *SMD* of 0.11. This indicates that students exposed to the intervention perceived more engagement from parents or caregivers in school-related matters—an important outcome given the role of family–school partnerships in supporting youth development.

Although not statistically significant, students in Cohort 1 also reported moderately higher levels of perceived fairness (ß = 0.012, *p* = .506) and SEL-related support from adults and peers (ß = 0.016, *p* = .347). While these estimates do not meet conventional thresholds for significance, their positive direction and consistency with the significant outcomes may suggest broader trends toward more inclusive and supportive school environments following the intervention.

By contrast, there was no evidence that the intervention influenced academic motivation (ß = –0.001, *p* = .923). This suggests that while the program may strengthen school climate and relational supports, it may not directly affect students' motivation for academic engagement—at least not in the short term. Future studies could examine whether changes in school climate mediate longer-term academic outcomes or whether complementary instructional supports are needed to shift motivation-related constructs directly.

School context also played a significant role. Students attending urban schools reported significantly lower levels of school connectedness, safety, and SEL supports compared to their peers in non-urban settings. Similarly, attending a school with a higher percentage of students eligible for FRPL was negatively associated with several outcomes, including perceived fairness and school belonging. These findings underscore the potential influence of broader socioeconomic and structural factors on students' school experiences.

Conversely, higher school-level achievement—as measured by the percentage of students meeting ELA standards—was positively associated with student-reported SEL and climate outcomes. In particular, schools with higher academic performance tended to have students who reported greater levels of perceived support, safety, and positive behavior climate. These associations suggest that academic and social and emotional conditions within schools may reinforce one another and that schoolwide achievement may reflect broader organizational health.

Discussion

In this study, we examined the effects of the California Integrated Supports Project (CA-ISP) on student-level disciplinary outcomes using a rigorous quasi-experimental design with propensity score weighting, multilevel modeling, and school climate and well-being outcomes using mixed-effects models with baseline equivalence. Drawing on a large administrative dataset for the disciplinary exclusions, we estimated the impact of CA-ISP implementation on six primary outcomes: the total number of disciplinary incidents, a disciplinary incident occurrence, in-school suspension (ISS) and out-of-school suspension (OSS) occurrence, and the number of days missed due to ISS and OSS. Results from linear and logistic mixed-effects models indicated statistically significant improvements in several key student

discipline outcomes associated with CA-ISP implementation, supporting the hypothesis that integrated Multi-tiered Systems of Support can reduce exclusionary discipline.

These findings contribute to a growing literature suggesting that coordinated approaches to behavioral support, such as Positive Behavioral Interventions and Supports (PBIS) and its extensions, can improve school climate and student outcomes (Bradshaw et al., 2010; Sugai & Horner, 2009). Specifically, the observed reduction in the probability of receiving an ISS or OSS (with *OR*s of 0.641 and 0.573, respectively) and significant decreases in logged days missed due to suspension suggest that CA-ISP may mitigate exclusionary discipline practices. These effects were observed after adjusting for a comprehensive set of student- and school-level covariates and controlling for time-invariant differences across schools and districts.

Consistent with prior research highlighting disparities in school discipline (Gregory et al., 2010; Losen et al., 2015), our baseline models revealed substantial variation in discipline outcomes across schools and districts, as reflected in the intraclass correlation coefficients. This variation underscores the importance of school- and district-level factors in shaping disciplinary practices, and affirms the need for systems-level interventions like CA-ISP that embed behavioral supports within a broader equity-focused framework.

> *By fostering data-driven decision-making and shared leadership across education and mental health professionals, CA-ISP appears to have enhanced schools' capacity to prevent and address behavioral challenges proactively.*

The reduction in disciplinary incidents and suspensions aligns with the goals of the Interconnected Systems Framework (ISF), which integrates school-based mental health supports with PBIS (Barrett et al., 2013; Cook et al., 2015). By fostering data-driven decision-making and shared leadership across education and mental health professionals, CA-ISP appears to have enhanced schools' capacity to prevent and address behavioral challenges proactively. The magnitude of these effects—e.g., a standardized mean difference of 0.27 for total disciplinary incidents—suggests a modest yet meaningful improvement in student behavioral outcomes, consistent with Kraft's (2020) framework, indicating that effect sizes of 0.20–0.49 are educationally relevant.

The findings from the school climate analyses contribute to a growing body of evidence suggesting that implementing school-based social and emotional learning (SEL) practices, along with culturally sustaining and trauma-informed practices, can positively influence students' perceptions of safety, connectedness, and school climate. Although the effect sizes were modest (*g*'s ≈ 0.10), they are comparable to those observed in other large-scale SEL studies implemented in diverse school settings (Durlak et al., 2011; Taylor et al., 2017). Improvements in perceived school safety and belonging are especially meaningful given their strong associations with academic engagement, reduced risk behaviors, and overall student well-being (Thapa et al., 2013). That students in CA-ISP school also reported greater perceived parent involvement is noteworthy, as family–school partnerships are recognized as a critical, yet often underleveraged, component of whole-child approaches to school improvement (Christenson & Sheridan, 2001; Weiss et al., 2006). The results suggest that the intervention may have fostered more inclusive school environments that extended relational supports beyond the classroom.

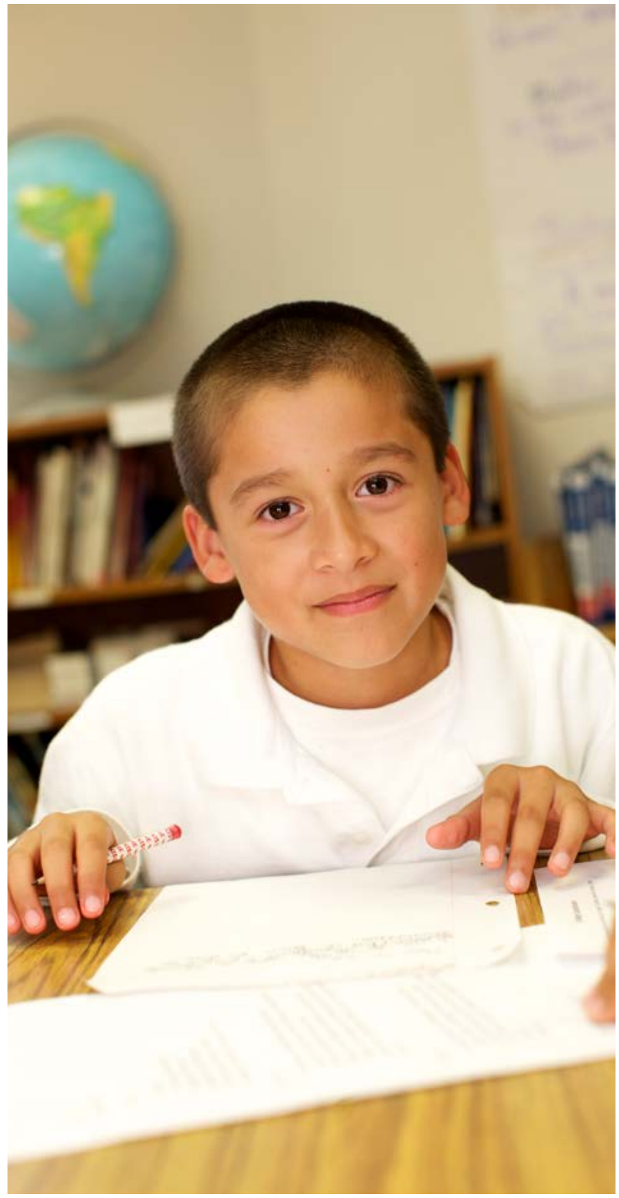
At the same time, the absence of significant effects on academic motivation underscores the limits of standalone climate-focused programming. While SEL interventions can improve students' sense of connection and interpersonal functioning, academic mindsets may require more targeted, instructional supports or may emerge only over longer durations (Yeager & Walton, 2011; McKown, 2019). Furthermore, the observed disparities by school urbanicity and socioeconomic context point to the influence of structural inequities that shape students' school experiences independent of individual or classroom-level programming. Students attending urban or high-poverty schools reported consistently lower levels of safety, fairness, and SEL supports, echoing longstanding research showing that school climate disparities often mirror broader opportunity gaps (Gregory et al., 2010; Berkowitz et al., 2017). These findings highlight the importance of integrating SEL initiatives with systemic equity efforts to ensure that all students—not just those in well-resourced settings—experience supportive, safe, and connected learning environments.

Despite these encouraging findings, several limitations should be noted. First, although propensity score weighting improves covariate balance between treated and untreated groups for the disciplinary exclusion models, residual confounding due to unobserved variables cannot be ruled out. For instance, schools opting into CA-ISP may differ in motivation, leadership, or resource availability in ways not captured in the available data. Second, administrative discipline records, while comprehensive, may underreport informal disciplinary actions or reflect inconsistent coding practices across districts. Third, the analytic approach relied on log transformations to address skew and zero inflation in count outcomes; while appropriate, this transformation complicates interpretation for practitioners and policymakers. Finally, model convergence warnings in some logistic models signal potential estimation challenges, though sensitivity analyses confirmed the robustness of key findings.

Recommendations for policy and practice include continued investment in and evaluation of integrated behavioral support systems. CA-ISP's emphasis on cross-sector collaboration and capacity building may be especially beneficial in high-need schools where mental health and behavioral supports have historically been under-resourced. Scaling up these efforts should involve ongoing technical assistance, fidelity monitoring, and alignment with broader equity initiatives. In addition, future research should examine the mechanisms through which CA-ISP impacts student outcomes, including changes in teacher practices, school climate, and student engagement, as well as potential differential effects by student subgroups.

CA-ISP can help schools create safer, more inclusive environments conducive to learning.

In conclusion, this study provides empirical support for CA-ISP as a promising statewide initiative that reduces exclusionary disciplinary practices. By integrating behavioral and mental health supports within a tiered framework, CA-ISP may help schools create safer, more inclusive environments conducive to learning. These findings reinforce the importance of systemic, equity-oriented interventions in promoting positive outcomes for all students and offer a model for other states seeking to advance school-based behavioral health integration.



References

Atkins, D. C., & Gallop, R. J. (2007). Rethinking how family researchers model infrequent outcomes: A tutorial on count regression and zero-inflated models. *Journal of Family Psychology*, *21*(4), 726–735. https://doi.org/10.1037/0893-3200.21.4.726

Austin, P. C., & Stuart, E. A. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in Medicine*, *34*(28), 3661–3679. https://doi.org/10.1002/sim.6607

Bal, A., Schrader, E. M., Afacan, K., Thorius, K. A. K., & Obiakor, F. (2021). *Cultural responsiveness field guide: Resources for trainers and coaches of positive behavioral interventions and supports (PBIS)* (2nd ed.). Center on PBIS, University of Oregon. https://www.pbis.org/resource/cultural-responsiveness-field-guide-resources-for-trainers-and-coaches

Barrett, S., Eber, L., McIntosh, K., Perales, K., Romer, N., & Thompson, M. (2013). *Interconnected systems framework: A new model to integrate school mental health and PBIS*. Center for Positive Behavioral Interventions and Supports. https://www.pbis.org/resource/interconnected-systems-framework-brief

Barrett, S., Eber, L., & Weist, M. (2013). *Advancing education effectiveness: Interconnecting school mental health and school-wide positive behavior support*. Center for Positive Behavioral Interventions and Supports. https://www.pbis.org/resource/interconnected-systems-framework-advancing-education-effectiveness

Barrett, S., Maras, M., Teodoro, P., Pohlman, K., Bavone, S., Cowen, S., & Eber, L. (2018). District scale up of school behavioral health: Impact of school-wide positive behavior interventions and supports and school-based mental health. *International Journal of Environmental Research and Public Health*, *15*(6), 1106. https://doi.org/10.3390/ijerph15061106

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Berkowitz, R., Moore, H., Astor, R. A., & Benbenishty, R. (2017). A research synthesis of the associations between socioeconomic background, inequality, school climate, and academic achievement. *Review of Educational Research*, *87*(2), 425–469. https://doi.org/10.3102/0034654316669821

Bloom, H. S., Richburg-Hayes, L., & Black, A. R. (2007). Using covariates to improve precision for studies that randomize schools to evaluate educational interventions. Educational Evaluation and Policy Analysis, *29*(1), 30–59. https://doi.org/10.3102/0162373707299550

Bradshaw, C. P., Mitchell, M. M., & Leaf, P. J. (2010). Examining the effects of schoolwide positive behavioral interventions and supports on student outcomes. *Journal of Positive Behavior Interventions*, *12*(3), 133–148. https://doi.org/10.1177/1098300709334798

Chinn, S. (2000). A simple method for converting an odds ratio to effect size for use in meta-analysis. *Statistics in Medicine*, *19*(22), 3127–3131.

Choi, J. H., McCart, A. B., Miller, D. H., & Sailor, W. (2022). Issues in statewide scale up of a multi-tiered system of support. *Journal of School Leadership*, *32*(5), 514–536. https://doi.org/10.1177/10526846211067650

Christenson, S. L., & Sheridan, S. M. (2001). *Schools and families: Creating essential connections for learning*. Guilford Press.

Collaborative for Academic, Social, and Emotional Learning (CASEL). (2020). *SEL framework: What are the core competencies and key settings?* Collaborative for Academic, Social, and Emotional Learning. https://casel.org/fundamentals-of-sel/what-is-the-casel-framework/

Cook, C. R., Fiat, A. E., Larson, M., Daikos, C., Slemrod, T., Holland, E. A., Thayer, A. J., & Renshaw, T. L. (2018). Positive greetings at the door: Evaluation of a low-cost, high-yield proactive classroom management strategy. *Journal of Positive Behavior Interventions*, *20*(3), 149–159. https://doi.org/10.1177/1098300717753831

Cook, C. R., Lyon, A. R., Kubergovic, D., Browning Wright, D., & Zhang, Y. (2015). A support system for school-based behavioral health services: Implementation of school-wide positive behavioral interventions and supports and school mental health initiatives. *Advances in School Mental Health Promotion*, *8*(1), 27–41. https://doi.org/10.1080/1754730X.2014.978119

Cruz, R. A., Firestone, A. R., & Rodl, J. E. (2021). Disproportionality reduction in exclusionary school discipline: A best-evidence synthesis. *Review of Educational Research*, *91*(3), 397–431. https://doi.org/10.3102/0034654321995255

Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school-based universal interventions. *Child Development*, *82*(1), 405–432. https://doi.org/10.1111/j.1467-8624.2010.01564.x

Eber, L., Weist, M. D., Barrett, S., Barrett, C. A., Green, A. L., Splett, J. W., Stephan, S., & Paternite, C. E. (2019). Integrating school mental health and PBIS: Considerations for practice. School Psychology, *34*(5), 451–461. https://doi.org/10.1037/spq0000295

Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., & Tu, X. M. (2014). Log-transformation and its implications for data analysis. Shanghai Archives of Psychiatry, *26*(2), 105–109. https://doi.org/10.3969/j.issn.1002-0829.2014.02.009

Forman, S. G., Shapiro, E. S., Codding, R. S., Gonzalez, J. E., Reddy, L. A., Rosenfield, S. A. Sanetti, L. M. H., & Stoiber, K. C. (2013). Implementation science and school psychology. *School Psychology Quarterly*, *28*(2), 77–100. https://doi.org/10.1037/spq0000019

Gage, N. A., Grasley-Boy, N., George, H. P., Childs, K., & Kincaid, D. (2019). A quasi-experimental design analysis of the effects of school-wide positive behavior interventions and supports on discipline in Florida. *Journal of Positive Behavior Interventions*, *21*, 50–61. https://doi.org/10.1177/1098300718768208

Gage, N. A., Lewis, T. J., Johnson, N. L., & Way, G. T. (2024). The impact of the Missouri school-wide positive behavior support (MO SW-PBS) on disciplinary exclusions. Journal of Positive Behavior Interventions, *27*(2), 82–93. https://doi.org/10.1177/10983007241275691

Gage, N. A., Salomonson, K., Ballew, T., Clavenna-Deane, B., & Grasley-Boy, N. (2023). *The impact of multi-tiered systems of support (MTSS) on student attendance and behavior*. WestEd.

Gregory, A., Cornell, D., & Fan, X. (2010). The relationship of school structure and support to suspension rates for Black and White high school students. *American Educational Research Journal*, *48*(4), 904–934. https://doi.org/10.3102/0002831210397986

Gregory, A., Skiba, R. J., & Noguera, P. A. (2010). The achievement gap and the discipline gap: Two sides of the same coin? *Educational Researcher*, *39*(1), 59–68. https://doi.org/10.3102/0013189X09357621

Hoover, S. A., Lever, N., Sachdev, N., Bravo, N., Schlitt, J., Acosta Price, O., Sheriff, L., & Cash, A. (2020). Advancing comprehensive school mental health: Guidance from the field. School Mental Health, 12, 176–191. https://doi.org/10.1007/s12310-020-09343-0

Horner, R. H., Sugai, G., Smolkowski, K., Eber, L., Nakasato, J., Todd, A. W., & Esperanza, J. (2009). A randomized, wait-list controlled effectiveness trial assessing school-wide positive behavior support in elementary schools. *Journal of Positive Behavior Interventions*, *11*(3), 133-144. https://doi.org/10.1177/1098300709332067

Kraft, M. A. (2020). Interpreting effect sizes of education interventions. Educational Researcher, 49(4), 241–253.

Lee, A., & Gage, N. A. (2020). Updating and expanding systematic reviews and meta-analyses on the effects of school-wide positive behavior interventions and supports. Psychology in the Schools, *57*, 783–804. https://doi.org/10.1002/pits.22336

Lee, A., Gage, N. A., McLeskey, J., & Huggins-Manley, A. C. (2021). The impacts of school-wide positive behavior interventions and supports on school discipline outcomes for diverse students. *The Elementary School Journal*, *121*, 410–429. https://doi.org/10.1086/712625

Losen, D. J., & Haynes, L. S. E. (2016). Eliminating excessive and disparate school discipline: A review of research and policy reform. In: Skiba, R., Mediratta, K., & Rausch, M. (Eds). *Inequality in School Discipline*. Palgrave Macmillan. https://doi.org/10.1057/978-1-137-51257-4_14

Losen, D. J., Hodson, C. L., Keith II, M. A., Morrison, K., & Belway, S. (2015). Are we closing the school discipline gap? The Center for Civil Rights Remedies, UCLA Civil Rights Project. http://civilrightsproject.ucla.edu/resources/projects/center-for-civil-rights-remedies/school-to-prison-folder/federal-reports/are-we-closing-the-school-discipline-gap

Mager, U., & Nowak, P. (2012). Effects of student participation in decision making at school: A systematic review and synthesis of empirical research. *Educational Research Review*, *7*(1), 38–61. https://doi.org/10.1016/j.edurev.2011.11.001

McIntosh, K., Girvan, E. J., Horner, R. H., Smolkowski, K., & Sugai, G. (2018). Education not incarceration: A conceptual model for reducing racial and ethnic disproportionality in school discipline. *The Journal of Applied Research on Children: Informing Policy for Children at Risk*, *7*(2), Article 4. https://digitalcommons.library.tmc.edu/childrenatrisk/vol7/iss2/4

McIntosh, K., Massar, M. M., Algozzine, R. F., George, H. P., Horner, R. H., Lewis, T. J., & Swain-Bradway, J. (2016). Technical adequacy of the SWPBIS tiered fidelity inventory. Journal of Positive Behavior Interventions, *19*(1), 3–13. https://doi.org/10.1177/1098300716637193

McKown, C. (2019). Challenges and opportunities in the applied assessment of student social and emotional learning. Educational Psychologist, 54(3), 205–219. https://doi.org/10.1080/00461520.2019.1614446

Metz, A., Louison, L., & Ward, C. (2019). *The Hexagon Tool: Exploring context* (2nd ed.). National Implementation Research Network, University of North Carolina at Chapel Hill. https://nirn.fpg.unc.edu/resources/hexagon-exploration-tool

Muldrew, A. C., & Miller, F. G. (2021). Examining the effects of the personal matrix activity with diverse students. *Psychology in the Schools*, *58*(3), 515–533. https://doi.org/10.1002/pits.22461

National Center for Education Statistics. (2024). *Public Elementary/Secondary School Universe Survey 2023–24 v.1a* [Data set]. U.S. Department of Education. https://nces.ed.gov/ccd/elsi/tableGenerator.aspx

O'Malley, M., Voight, A., Renshaw, T. L., & Eklund, K. (2015). School climate, family structure, and academic achievement: A study of moderation effects. *School Psychology Quarterly*, *30*(1), 142–157. https://doi.org/10.1037/spq0000076

Osborne, J. W. (2010). Improving your data transformations: Applying the Box–Cox transformation. *Practical Assessment, Research, and Evaluation*, *15*(12), 1–9.

Paris, D., & Alim, H. S. (Eds.). (2017). *Culturally sustaining pedagogies: Teaching and learning for justice in a changing world*. Teachers College Press.

Sklad, M., Diekstra, R., Ritter, M. D., Ben, J., & Gravesteijn, C. (2012). Effectiveness of school-based universal social, emotional, and behavioral programs: Do they enhance students' development in the area of skill, behavior, and adjustment? *Psychology in the Schools*, *49*(9), 892–909. https://doi.org/10.1002/pits.21641

Splett, J. W., Lane, K. L., Weist, M. D., Fasching, L., Thompson, M. S., Carney, J. V., & Markowitz, L. (2024). The impact of the Interconnected Systems Framework on school climate: Results from a randomized controlled trial. School Psychology, 39(2), 83–96. https://doi.org/10.1037/spq0000567

Substance Abuse and Mental Health Services Administration (SAMHSA). (2014). *SAMHSA's concept of trauma and guidance for a trauma-informed approach (HHS Publication No. SMA14-4884)*. U.S. Department of Health and Human Services. https://ncsacw.samhsa.gov/userfiles/files/SAMHSA_Trauma.pdf

Sugai, G., & Horner, R. H. (2009). Responsiveness-to-intervention and school-wide positive behavior supports: Integration of multi-tiered system approaches. *Exceptionality*, *17*(4), 223–237. https://doi.org/10.1080/09362830903235375

Sugai, G., & Horner, R. H. (2019). Sustaining and scaling positive behavioral interventions and supports: implementation drivers, outcomes, and considerations. *Exceptional Children*, *86*(2), 120-136. https://doi.org/10.1177/0014402919855331

Taylor, R. D., Oberle, E., Durlak, J. A., & Weissberg, R. P. (2017). Promoting positive youth development through school-based social and emotional learning interventions: A meta-analysis of follow-up effects. *Child Development*, *88*(4), 1156–1171. https://doi.org/10.1111/cdev.12864

Thapa, A., Cohen, J., Guffey, S., & Higgins-D'Alessandro, A. (2013). A review of school climate research. Review of Educational Research, *83*(3), 357–385. https://doi.org/10.3102/0034654313483907

Tholander, M. (2011). Student-led conferencing as democratic practice. Children & Society, *25*(3), 239–250. https://doi.org/10.1111/j.1099-0860.2009.00277.x

U.S. Department of Education, Office for Civil Rights. (2025). *Protecting civil rights: Highlights of activities, Office for Civil Rights 2021–2025*. Washington, DC.

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). MICE: Multivariate imputation by chained equations in R. Journal of Statistical Software, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Weiss, H. B., Caspe, M., & Lopez, M. E. (2006). *Family involvement in early childhood education*. Harvard Family Research Project.

Weist, M. D., Figas, K., Stern, K., Terry, J., Scherder, E., Collins, D., & Stevens, R. (2022). Advancing school behavioral health at multiple levels of scale. *Pediatric Clinics of North America*, *69*(4), 725–737. https://www.sciencedirect.com/science/article/pii/S0031395522000396

Weist, M. D., Garbacz, S. A., Lane, K. L., McIntosh, K., & Stokes, H. (2022). Aligning and integrating school mental health and PBIS: Findings from a multi-site implementation study. *Journal of Adolescent Health*, *70*(2), 289–297.

Weist, M. D., Splett, J. W., Halliday, C. A., Gage, N. A., Seaman, M. A., Perkins, K. A., Perales, K., Miller, E., Collins, D., & DiStefano, C. (2022). A randomized controlled trial on the interconnected systems framework for school mental health and PBIS: Focus on proximal variables and school discipline. *Journal of School Psychology*, *94*, 49–65. https://doi.org/10.1016/j.jsp.2022.08.002

Welsh, R. O. (2023). Up the down escalator? Examining a decade of school discipline reforms. *Children and Youth Services Review*, *150*, 106962. https://doi.org/10.1016/j.childyouth.2023.106962

WestEd. (2023). *California healthy kids survey: Overview and survey content*. California Department of Education. https://calschls.org/surveys/chks/

Wiglesworth, M., Humphrey, N., & Lendrum, A. (2020). The impact of universal school-based social and emotional learning on teachers' affective well-being: A systematic review and meta-analysis. *Educational Psychology Review*, *32*(2), 511–538. https://doi.org/10.1007/s10648-019-09489-4

Yeager, D. S., & Walton, G. M. (2011). Social-psychological interventions in education: They're not magic. *Review of Educational Research*, *81*(2), 267–301. https://doi.org/10.3102/0034654311405999

Yeager, D. S., Purdie-Vaughns, V., Garcia, J., Apfel, N., Brzustoski, P., Master, A., Hessert, W. T., Williams, M. E., & Cohen, G. L. (2014). Breaking the cycle of mistrust: Wise interventions to provide critical feedback across the racial divide. *Journal of Experimental Psychology: General*, *143*(2), 804–824. https://doi.org/10.1037/a0033906

Appendix: Data Tables

Table 1. Descriptive Statistics by Year

Characteristics	2022–2023		2023–2024	
	Treatment	Control	Treatment	Control
n students	16,590	83,879	16,770	79,914
n schools	28	139	28	138
Enrollment	595.16 (147.85)	975.92 (643.11)	597.68 (148.02)	920.08 (617.92)
Pupil/Teacher Ratio	22.12 (2.7)	21.94 (2.7)	22.18 (2.68)	22 (2.78)
FRPL	0.63 (0.26)	0.65 (0.23)	0.63 (0.26)	0.65 (0.23)
Female	0.48 (0.02)	0.48 (0.03)	0.48 (0.02)	0.48 (0.03)
AI	0 (0.01)	0 (0)	0 (0.01)	0 (0)
AS	0.1 (0.1)	0.07 (0.08)	0.1 (0.1)	0.07 (0.09)
HP	0.48 (0.28)	0.51 (0.3)	0.48 (0.28)	0.51 (0.31)
BL	0.09 (0.09)	0.06 (0.06)	0.1 (0.09)	0.06 (0.06)
WH	0.24 (0.19)	0.29 (0.23)	0.23 (0.19)	0.29 (0.24)
Two	0.08 (0.06)	0.06 (0.04)	0.08 (0.06)	0.06 (0.04)
ELL	25.02 (18.4)	20.69 (17.9)	23.42 (16.89)	22.17 (17.88)
SWD	13.17 (4.2)	13.44 (6.41)	13.93 (3.59)	13.97 (6.42)
Charter School	0	2.3	0	2.5
ELA % Benchmark	32.49 (15.13)	39.62 (17.57)	32.57 (14.89)	36.94 (16.83)
Math % Benchmark	26.1 (17.98)	22.8 (15.1)	27.08 (18.13)	22.93 (15.47)
School Level and Locale	**%**	**%**	**%**	**%**
School Level				
Elementary	84	43.7	83.8	46.4
Middle	16	15.7	16.1	17.2
High	0	38.8	0	34.8
Locale				
Urban	3.8	18.3	4	14.1
Suburban	84.8	67.5	84.6	70.5
Town	3.3	0	3.3	0
Rural	8.1	14.2	8.1	15.4

Table 2. California Healthy Kids Survey (Elementary) – Subscale Overview and Reliability

Subscale	# of Items	Sample Items	a
School Connectedness	4	Do you feel close to people at school? Are you happy to be at this school? Do teachers treat students fairly at school?	0.68
Caring Staff–Student Relationship	6	Do the teachers and other grown-ups at school care about you? Do they listen when you have something to say? Do they try to know you?	0.79
School High Expectations	3	Do teachers tell you when you do a good job? Do they believe in you? Do they want you to do your best?	0.73
Student Meaningful Participation	7	Are you asked about your ideas? Do you get to help decide activities? Do you do helpful things at school?	0.75
Overall School Environment	Composite	(Combination of School Connectedness, Caring Relationships, High Expectations, Meaningful Participation)	0.74
Home High Expectations	2	Do your parents expect you to do your best? Do they believe you will succeed?	0.70
Academic Motivation	4	I try hard to be good at schoolwork. I keep working even when it's hard. I feel good when I learn something new.	0.76

Subscale	# of Items	Sample Items	a
Fairness	4	◢ Are students treated fairly when they break rules? ◢ Are students treated fairly regardless of race or gender?	0.72
Social and Emotional Learning Support	4	◢ Is there an adult who helps you solve problems? ◢ Do teachers teach you to solve arguments? ◢ Do teachers help you calm down?	0.75
Antibullying Climate	3	◢ Do teachers make it clear bullying isn't allowed? ◢ Are students taught that bullying isn't allowed? ◢ Is there an adult you can talk to?	0.61
Prosocial Behavior	4	(Items reflect encouragement and modeling of prosocial behavior by staff and students)	0.78
Parent Involvement in Schooling	5	(Items reflect communication and involvement between families and school staff)	0.71

Note: Reli = reliability; Reliability from 2017–2018 Elementary California Healthy Kids Survey *https://calschls.org/docs/measurementstructurecalschls_final.pdf*

Table 3. Skewness of Outcome Variables Under Different Transformations

Outcome Variable	Raw Skewness	√ (Square Root)	³√ (Cube Root)	log1p (Natural Log +1)
Behavior Incidents	9.93	4.03	2.76	3.12
Days Missed for ISS	22.71	11.65	10.61	12.35
Days Missed for OSS	13.31	6.09	5.13	5.83

Note: ISS is in-school suspension and OSS is out-of-school suspension

Table 4. Linear Mixed-effects Model for the Total Number of Discipline Incidents

Predictor	Estimate	SE	t-value	p-value	Exp	Interpretation
Intercept	0.038	0.056	0.678	0.501	1.039	Baseline mean (log scale)
Treatment	-0.055	0.067	-0.816	0.416	0.947	Difference at baseline
Time	0.061	0.003	21.527	< .001	1.062	Change over time (control)
Treatment x Time	-0.086	0.004	-20.58	< .001	0.918	Difference-in-differences effect

Note: Model included all student and school covariates, inverse probability of treatment weights, and random effects for school and district.

Table 5. Logistic Mixed-effects Model Predicting Any Discipline Incident

Predictor	Estimate	SE	z-value	p-value	OR	Interpretation
Intercept	–5.922	0.529	–11.19	< .001	–	Baseline mean (log odds scale)
Treatment	–0.893	0.378	–2.37	.018	0.409	Difference at baseline
Time	0.264	0.015	17.25	< .001	1.303	Change over time (control)
Treatment x Time	–0.515	0.023	–22.24	< .001	0.597	Difference-in-differences effect

Note: Model included all student and school covariates, inverse probability of treatment weights, and random effects for school and district.

Table 6. Linear Mixed-effects Model for the Number of Days Missed for In-school Suspension

Predictor	Estimate	SE	t-value	p-value	Exp	Interpretation
Intercept	-0.007	0.007	-1.116	0.264	0.993	Baseline mean (log scale)
Treatment	0.002	0.003	0.851	0.395	1.002	Difference at baseline
Time	0.001	0.001	0.933	0.351	1.001	Change over time (control)
Treatment x Time	-0.007	0.001	-7.217	< .001	0.993	Difference-in-differences effect

Note: Model included all student and school covariates, inverse probability of treatment weights, and random effects for school and district.

Table 7. Logistic Mixed-effects Model Predicting Any In-school Suspensions

Predictor	Estimate	SE	z-value	p-value	OR	Interpretation
Intercept	-13.32	2.115	-6.30	< .001	–	Baseline mean (log odds scale)
Treatment	-0.344	0.449	-0.77	.442	0.709	Difference at baseline
Time	0.072	0.048	1.51	.132	1.075	Change over time (control)
Treatment x Time	-0.444	0.063	-7.06	< .001	0.641	Difference-in-differences effect

Note: Model included all student and school covariates, inverse probability of treatment weights, and random effects for school and district.

Table 8. Linear Mixed-effects Model for the Number of Days Missed for Out-of-school Suspension

Predictor	Estimate	SE	t-value	p-value	Exp	Interpretation
Intercept	0.11	0.028	3.87	0.0002	1.116	Baseline mean (log scale)
Treatment	-0.031	0.017	-1.86	0.0659	0.969	Difference at baseline
Time	-0.004	0.002	-2.47	0.0135	0.996	Change over time (control)
Treatment x Time	-0.031	0.003	-11.68	< .001	0.969	Difference-in-differences effect

Note: Model included all student and school covariates, inverse probability of treatment weights, and random effects for school and district.

Table 9. Logistic Mixed-effects Model Predicting Any Out-of-school Suspensions

Predictor	Estimate	SE	z-value	p-value	OR	Interpretation
Intercept	-5.413	0.761	-7.11	< .001	–	Baseline mean (log odds scale)
Treatment	-0.340	0.221	-1.54	.123	0.712	Difference at baseline
Time	-0.030	0.024	-1.27	.206	0.970	Change over time (control)
Treatment x Time	-0.556	0.036	-15.57	< .001	0.573	Difference-in-differences effect

Note: Model included all student and school covariates, inverse probability of treatment weights, and random effects for school and district.

Table 10. Treatment Effects on Student-reported Outcomes from Linear Mixed-effects Models

Outcome	B (Cohort 1)	SE	t	p
School Connectedness	0.016	0.015	1.088	.277
Caring Staff–Student Relationship	0.036	0.018	1.969	.049 *
School High Expectations	0.027	0.013	2.000	.046 *
Academic Motivation	–0.001	0.013	–0.096	.923
Fairness	0.012	0.018	0.665	.506
SEL Support	0.016	0.017	0.941	.347
Parent Involvement in Schooling	0.029	0.012	2.431	.015 *
Antibullying Climate	0.028	0.015	1.828	.068
Prosocial behavior	0.0002	0.010	0.015	.988

*Note: Each coefficient represents the estimated effect of being in treatment (vs. comparison) on the outcome from a separate linear mixed-effects model. All models control for grade, school urbanicity, school level, FRPL, total enrollment, school racial and ethnic composition, and prior school-level ELA achievement. Random intercepts for school and district were included. *p < .05*

Table 11. Standardized Mean Difference Effect Sizes for Cohort 1 on Student-reported Outcomes

Outcome	B (Cohort 1)	SD (Control Group)	Effect Size (g)
Caring Staff–Student Relationship	0.036	0.350	0.10
School High Expectations	0.027	0.270	0.10
Parent Involvement in Schooling	0.029	0.262	0.11

Note: B represents the unstandardized coefficient for the Cohort 1 group from the linear mixed-effects model. SMDs were calculated using the standard deviation of the outcome in the comparison (Cohort 0) group. All models included covariate adjustment and random intercepts for school and district. SMDs reflect between-group differences expressed in standard deviation units.

Suggested citation: Gage, N. A., Ulrich, T. G., Wong, L., Grasley-Boy, N., & LeBoyd, N. (2025). *The initial impacts of the California Integrated Supports Project on student outcomes.* WestEd.

WestEd is a nonpartisan, nonprofit organization that aims to improve the lives of children and adults at all ages of learning and development. We do this by addressing challenges in education and human development, increasing opportunity, and helping build communities where all can thrive. WestEd staff conduct and apply research, provide technical assistance, and support professional learning. We work with early learning educators, classroom teachers, local and state leaders, and policymakers at all levels of government.

For more information, visit WestEd.org. For regular updates on research, free resources, solutions, and job postings from WestEd, subscribe to the E-Bulletin, our semimonthly e-newsletter, at WestEd.org/subscribe.